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Decision Support for Team Building: Incorporating Trust into a Recommender-Based Approach

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Abstract

In this paper we present a novel automated recommendation approach to support the selection of individuals to teams. Recent organizational trends show an increasing importance of team-based work structures and more and more companies use this team-focused structure with the hope to increase organizational effectiveness. Whereas traditional selection systems are focused on finding a match between job requirements and individuals' abilities, these systems need to be changed in order to reflect the enhanced requirements when selecting individuals to work in teams. This is important as teamwork requires interaction among its members and not just co-action. Our approach is therefore based on two dimensions. First, people need to be matched to jobs for which they possess the right knowledge, skills and abilities to fulfill all tasks. Second, people need to fit with the other people they are supposed to work with in terms of interpersonal compatibility. Based on an adapted probabilistic latent aspect model and a trust computational model we present a first prototype aiming to support the systematic selection of individuals to form effective teams.

Keywords: Team Building, Decision Support, Personnel Selection, Recommender System

1. Introduction

Organizations nowadays are faced with fast changing organizational structures, flexible working styles, increasing importance of team-based work structures and the evolution of new kinds of jobs (Anderson et al. 2004). Modern information and communication technologies reduce coordination costs and support a shift towards collaborative networks of people and concepts such as virtual work and virtual organizations (DeSanctis and Monge 1999). Employees are more loosely affiliated with organizations as jobs are more and more organized in projects (Beck 2002; DiTomaso 2001).

Whereas in the past people used to be recruited to fill a specific role with more or less clearly defined tasks and responsibilities (Werbel and Gilliland 1999), employees are nowadays recruited for a variety of possible roles they might have to fill during their employment, working in several different teams (Anderson et al. 2004).

When selecting individuals from external or internal sources to those teams, HR personnel in large companies are usually faced with the problem of having huge amounts of candidate profiles which makes a manual search to find the best fitting candidate impossible. Thus our research question is: What are the requirements for a decision support system for team building?

Existing IS-supported approaches to facilitate the search for qualified candidates are mainly based on simple keyword-based search functionality or only consider unary attributes that are directly tied to an individual. We argue that a decision support system for team building additionally needs to consider relational attributes such as trust in order to determine a fit between the candidate and existing team members. Therefore we present a first prototype that incorporates trust into a recommender-based approach for personnel selection. We believe that this can lead to competitive advantage as it increases the matching quality and supports the selection of individuals to teams.

The remainder of the paper is organized as follows. We first give an overview of relevant factors to be considered when composing effective teams and derive requirements for an IS-supported solution before discussing existing approaches (section 2). Afterwards, a trust computational model is presented, incorporating trust into an automated recommendation approach (section 3). We finally present a first prototype aiming to support the personnel selection in order to form effective teams.

2. Requirements for IS-Supported Team Building and Actual Approaches

Recent research showed the increasing importance of information technology for human resource processes in general and recruiting processes in particular (Keim et al. 2005).

However, searching these data usually happens based on keyword matches that cannot lead to good results as personnel selection usually depends on underlying attributes such as personal characteristics or social skills (Jackson 1996) as well as on relational aspects such as interpersonal compatibility. In this context literature usually distinguishes between (1) person-job, (2) person-team and (3) person-organization fit. The latter covers the fit between the candidate and the organizational culture and norms (Chatman 1989; Kristof 1996). However, as we focus on an internal team staffing scenario we can neglect the person-organization fit, assuming that it was considered when initially hiring the employee. Thus, an approach that supports the team composition task must cover aspects of person-job fit as well as of person-team fit (Werbel and Johnson 2001). The two concepts are briefly presented hereunder and then used to derive requirements for an IS-supported team building approach.

2.1. *Person-Job Fit*

Literature intensively discusses influencing factors that determine a good person-job fit. Among the most discussed aspects are (1) individual skills, knowledge and abilities specific to the respective job, (2) general mental abilities and (3) personality aspects (Anderson et al. 2004; Salgado et al. 2003). Typical personnel selection methods to assess these factors are CV-screening, review of references, interview, assessment center, work sample test, GMA test and personality test (Albert 2004; Salgado 1999).

In this context, Jackson (1996) discusses the difficulties of evaluating and measuring human attributes due to their complexity. A good fit often depends on underlying aspects which are usually hard to measure. Autor (2001) hereby distinguishes between low bandwidth data such as education, credentials and experience and high bandwidth data such as motivation and cultural fit. As the latter typically requires personal interaction to be measured, Autor sees this as one important reason why information systems have not been extensively used in the area of personnel selection so far (see also West 1994).

2.2. *Person-Team Fit*

As teamwork requires interaction among the team members and not just co-action (Guzzo 1996; Werbel and Johnson 2001), person-team fit in addition to person-job fit needs to be considered when composing teams (see also Cho et al. 1994; Tihanyi et al. 2000).

Some authors argue that a good fit occurs if the employees have supplementary attitudes, skills, abilities and preferences (Muchinsky and Monahan 1987) leading to group cohesiveness and faster decision processes (Evans and Dion 1991; Werbel and Johnson 2001).

Others promote complementary and diverse skills as diversity increases the possibility for innovation and creativity and can complement deficiencies of one team member with the strength of others (Tziner 1988; Watson et al. 1993).

A common understanding exists that interpersonal cooperation and communication are important aspects for the effectiveness of teamwork (Dunphy and Bryant 1996; Jones and George 1998). MacAllister (1995) and Jones and George (1998) argue that the required level of interpersonal cooperation in turn requires a high level of trust among the team members thus noting that trust is a factor that cannot be neglected when composing teams.

2.3. Requirements for an IS-Supported Team Building Approach

Based on the two described concepts of fit we conclude that an IS-supported approach to team building needs to account for two dimensions. It must (1) consider unary attributes such as individual skills, mental abilities and personality that determine the fit between the individual and the tasks to be accomplished, as well as (2) relational attributes that determine the fit between the individual and the upcoming team members.

We derive the following three major requirements when recommending candidates to form effective teams:

1. Recommending people is a bilateral process that needs to take into account the preferences not only of a single person (e.g. the HR expert), but also of several persons (e.g. the candidate and existing team members).
2. Recommendations cannot be based on the attributes tied to persons in consideration only, but need to consider relational aspects that determine the fit between the person and the team members.
3. As every individual is considered to be unique, we cannot select a single person several times. Recommendations of candidates to form teams therefore need to incorporate “content”-elements such as the unary and relational attributes mentioned above.

These requirements are different from traditional recommendation scenarios where *objects* are recommended, as here we want to recommend *subjects*. Based on these findings we developed a first prototype incorporating unary and relational attributes into a recommender-based approach aiming to support the team building process.

2.4. Actual Approaches

The complexity of team building as described above explains the lack of existing commercial software products. Most available systems are based on simple keyword-based search and filter techniques using standard database queries.

A more innovative approach is presented by Lang and Pigneur (1999) who developed an intranet-based marketplace for human competencies that are represented by competency trees. The actual matching, however, is still based on standard database queries in order to find employees that match with the search criteria.

A very interesting approach to IS-supported personnel selection is presented by Färber et al. (2003) who developed a probabilistic model that provides an automated recommendation of candidates. As we utilize and extend this model in our novel decision support system for team building, the probabilistic approach is briefly presented in the following.

2.5. A Probabilistic Approach for Predicting Person-Job Fit

Automated recommendation systems were originally developed for information retrieval purposes. They face the problem of information overload by assisting customers in finding the products or services that match with her/his preferences. Commonly used methods in this context are based on content-based and/or collaborative filtering techniques (Resnick and Varian 1997; Sarwar et al. 2001).

Färber et al. (2003) applied such a recommendation system originally used to recommend *objects* to users (such as movies or books) to a partner-matching scenario thus recommending *subjects*. Their probabilistic hybrid recommendation model is adapted from the probabilistic latent semantic analysis (PLSA) as described by Hofmann (1999) and Hofmann and Puzicha (1999). The PLSA model interprets the preferences of users as convex combination of underlying latent aspects.

Figure 1 shows a graphical representation of the latent aspect model applied to the context of partner matching. The model parameters are estimated using the Expectation Maximization (EM) algorithm (Dempster et al. 1977) with x representing the recruiter with the job description and a representing attributes of the candidate y composed of a quadruple such as $a = (\text{"mathematical skills"}, \text{"diploma grade"}, \text{"1.0"}, \text{"University of Frankfurt"})$. The latent aspect is considered in the model using the latent variable $z \in Z\{z_1, \dots, z_k\}$.

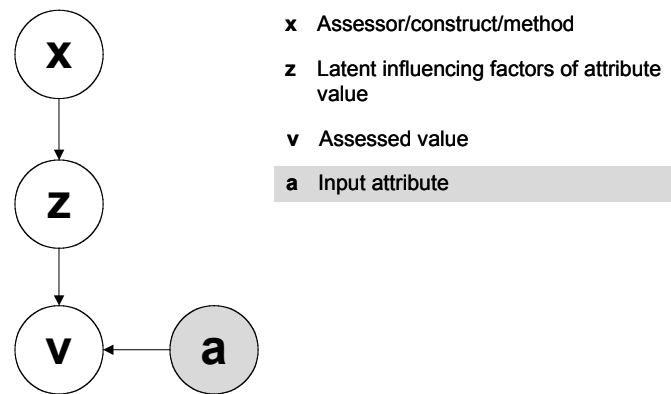


Figure 1. The Candidate Recommendation Model (Färber et al. 2003)

The model finally results in a rating matrix $R' = r'_{x,y,v}$ containing the probability that recruiter x rates candidate y with value v . Latter could be any value or – in the simplest case – just be defined as $v \in V = \{\text{"qualified"}, \text{"not qualified"}\}$.

This probabilistic approach automatically recommends candidates that fit best to a job position based on past rating data and considering underlying aspects. However, the model has some weaknesses as it is focused only on unary candidate attributes that are directly tied to the individual thus only predicting person-job fit. It does not consider relational information to evaluate the person-team fit.

We therefore extend this model by incorporating trust into the recommender-based approach in order to add relational information. We expect this to increase the prediction quality for the selection of individuals to form teams.

3. A Relational Recommender for Predicting Person-Team Fit

The previously described recommendation approach neglects relational aspects that are important to predict person-team fit as already discussed. In this context, trust relations

among team members are seen as important relational factor by many researchers as they directly influence interpersonal cooperation (Jones and George 1998; McAllister 1995). Thus, in order to incorporate trust into the recommender-based approach, we developed a trust computational model as described in the following.

3.1. A Trust Computational Model

Conforming to Richardson et al. (2003) we assume that trust can be expressed in a singular value even if it is a quite complex and multidimensional phenomenon (see also Abdul-Rahman and Hailes 2000). As trust is a subjective impression that differs from person to person, each member builds his own personal web of trust (Guha et al. 2004; Khare and Rifkin 1997; Richardson et al. 2003).

We specify $t_{A,B}$ as trust user A holds for user B (Rahman and Hailes 2000) and constitute the values of $t_{A,B}$ to lie between 0 and 1 where 0 means that user A distrusts user B whereas 1 indicates that B is fully trustworthy (in the eyes of A). Based on literature that discusses how trust propagates through social networks (see for example Guha et al. 2004; Yu and Singh 2003) as well as based on own theoretical considerations, we define three different scenarios as depicted in Figure 2(a)-(c). The first figure shows a propagation scenario where -based on two given trust values- the trust propagates along an edge. In the scenarios 2(b) and (c) we try to predict trust values based on given information.

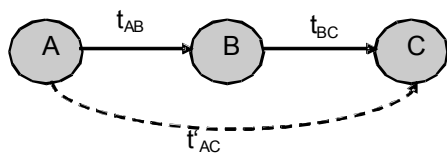


Figure 2(a): Direct Trust Propagation

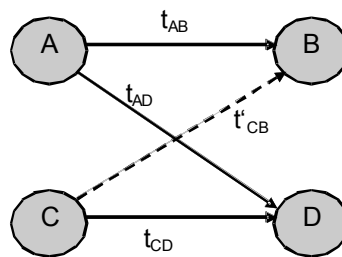


Figure 2(b): Collaborative Trust Prediction

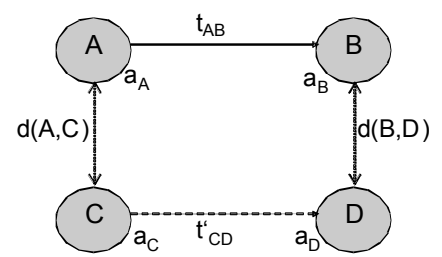


Figure 2(c): Similarity-based trust Prediction

The idea is that the different trust propagation and prediction models outlined above could serve as simple estimators for deriving unknown trust relations from known ones. It would be preferable to implement a machine-learning algorithm which implicitly learns the appropriate model from the empirical data it is supposed to use when forecasting or proposing new relationships. Whenever the relations given in the data exhibit significant transitivity, the model should learn this relation. To some extent empirical data will always comply in a strict sense while other properties only hold in the stochastic sense that the conditional probability for e.g. a trust relation between agent x and agent y is significantly higher when we know that x trusts z and z trusts y but it will never be sure.

As basis for the trust computational model we distinguish two different kinds of trust, explicit and similarity-based, which are explained in detail in the next sections.

3.2. Explicit Trust

As explicit trust we define trust ratings that have been explicitly stated by, for example, conducting a survey regarding interpersonal relationships among team members. In this paper we do not focus on how to conduct such kind of survey but instead assume that the ratings have already been assessed. Based on these given trust ratings we can predict so far unknown relations as depicted in Figure 2(a) and (b).

Former demonstrates what Guha et al. (2004) call “Direct propagation”. Assuming that candidate A trusts B with value t_{AB} and B trusts C with value t_{BC} , the direct propagation model infers that A trusts C as well (see also Richardson et al. 2003; Yu and Singh 2000). $t'_{AC}=t_{A \rightarrow B \rightarrow C}$ indicates that A trusts C using a path via B which is usually referred to as trust path. The preferred way to concatenate trust values lying on one common trust path is multiplication (Guha et al. 2004; Kamwar et al. 2003; Richardson et al. 2003), leading to the following equation:

$$t'_{AC}=t_{AB} \cdot t_{BC}$$

The second scenario (Figure 2(b)) shows a typical collaborative filtering situation. Based on the three given relations and assuming that $t_{AD} \approx t_{CD}$, the model concludes that candidate A and C have similar preferences as they both trust D with similar values. This information is then used to predict the missing relation between C and B . We use an adapted PLSA model to predict such collaborative trust recommendations resulting in a matrix $ET'=t'_{y,y,v}$, containing the probabilities that candidate y rates another candidate y with rating value $v = \{\text{“full trust”} = 1 \mid \text{“full distrust”} = 0\}$.

To summarize, given a set of explicit trust ratings, the direct propagation and the collaborative prediction rules allow the calculation of trust values for scenarios such as shown in Figure 2(a) and Figure 2(b). However, scenarios such as that depicted in Figure 2(c) cannot be used for trust calculation, as there is no direct or indirect trust path between the candidates in question (C and D).

3.3. Similarity-Based Trust

As similarity-based trust we define trust values that are based on preference similarities among individuals. Research constitutes a positive correlation between user similarity and established trust (Abdul-Rahman and Hailes 2000; Montaner et al. 2002). Jones and George (1998) note that people tend to trust other people more if they share the same values and attitudes. Ziegler and Lausen (2004) conclude, using data from an online book-reading community, that the more similar two users are, the greater their established trust.

In information retrieval, similarities between users are typically calculated using Pearson correlation, cosine vector similarity, or Spearman correlation methods (Breese et al. 1998; Herlocker et al. 1999).

In our case it makes sense to calculate similarities among employees based on their job preferences. We use an adapted PLSA model in the same way as used in the candidate recommendation scenario in order to predict job preferences based on previously rated jobs.

Following this approach, the latent aspects of the job preferences model can be used to create segments of similar users (Hofmann 1999). Xin et al. (2004) follow this idea by building segments of web users based on their visited pages. Compliant with this approach we build segments of candidates with similar preference structures based on the latent aspects retrieved from the rated job profiles. Hereby it is important to know that one user can belong to several segments in difference to clustering techniques (Hofmann 1999; Hofmann and Puzicha 1999). The similarity between two users can be calculated as follows:

$$sim_{AB} = \begin{cases} \frac{1}{n_z} \sum_{z \in Z} |P(A|z) - P(B|z)| & \text{if } n(I_A \cap I_B) \neq 0 \\ 0 & \text{otherwise} \end{cases}$$

where $P(A|z)$ is the ‘proximity’ to latent aspect z , n_z is the number of z variables and $n(I_A \cap I_B)$ is the number of co-rated job profiles between candidate A and B .

In plain words, we calculate the difference of the probabilities that two users belong to a segment constituted by a latent variable z . We sum up the differences for all latent aspects and divide through the number of segments. In case we have no co-rated job profiles between two users we cannot calculate any similarity value as the EM algorithm would not generate valuable results because it starts with random values that cannot be correctly adjusted if no co-rated job profiles are found (Hofmann and Puzicha 1999). Assuming a positive correlation between user similarity and trust we get $t'_{AB} = \text{sim}_{AB}$.

As the number of co-rated job profiles is an indicator for the accuracy of the predicted trust value we use it as weight factor to calculate the similarity-based trust. As example we want to discuss a scenario with three individual profiles A , B and C that have no explicit trust ratings assigned to each other. However, A and B as well as B and C have a common preference structure regarding their co-rated job profiles. These similarities in the preference structures are used to calculate similarity-based trust values. This allows us to estimate a so far unknown trust relation between A and C as follows (adapted from Papagelis et al. 2005):

$$t'_{AC} = t_{A \rightarrow B \rightarrow C} = \frac{n(I_A \cap I_B)}{n(I_A \cap I_B) + n(I_B \cap I_C)} t_{AB} + \frac{n(I_B \cap I_C)}{n(I_A \cap I_B) + n(I_B \cap I_C)} t_{BC}$$

In other words, to compute the inferred trust t'_{AC} , trust t_{AB} and t_{BC} are summed up, both weighted with the number of co-rated job profiles of each direct association. The computed value lies between the values of the two direct trust relations. If the amount of co-rated job profiles is changing, the trust value of the respective relation changes accordingly. The concept of dynamically changing trust is also discussed by Abdul-Rahman and Hailes (2000) who argue that additional evidence – in our case this means additional co-rated job profiles – “...may increase or decrease our degree of trust in another agent.”

The similarity-based approach allows us to calculate trust in a scenario such as depicted in Figure 2(c) where we directly combine individual and relational attributes. Based on the existing individual profiles A , B , C and D together with the existing trust relation t_{AB} , we can calculate similarities between user profile pairs ($d(x,y)$). With this information it is possible to predict a trust rating for the unknown relation t'_{CD} .

3.4. Trust Path Aggregation

As there might exist more than one trust path between individuals, literature discusses aggregation alternatives. Richardson et al. (2003) distinguish three different types of aggregation: Maximum value, minimum value and average. The maximum value approach takes the path with the highest trust and neglects all the others paths, which can be seen as very optimistic. The minimum value approach in turn is very pessimistic as it only takes the trust path with the lowest trust value. The average approach finally calculates an average using the trust values of all available paths (see also Guha et al. 2004; Kamvar et al. 2003).

We apply the latter in our model additionally utilizing the user's confidence in the trustworthiness of the various paths as weight (Papagelis et al. 2005). Confidence hereby is defined as reliability the user assigns to the association. So even if the calculated trust value t_{AB} is equal to t_{BA} (which is the case when processing similarity-based trust values as they are calculated using preference similarities), each user might have a different confidence in this relationship, reinforcing the idea of a subjective impression of trust into the model (Abdul-Rahman and Hailes 2000). We assume the degree of confidence to rise if the number of co-rated job profiles increases, leading to the deduction that a candidate's predicted trust in another candidate becomes more reliable if the number of co-rated job profiles is high. The most confident association, thus the one with the most co-rated job profiles, is therefore

initialized with 1 whereas all other direct associations are set in relation to this maximum value leading to the formulation (taken from Papagelis et al. 2005):

$$C_{AB} = \frac{n(I_A \cap I_B)}{n(I_A \cap I_{X_{MAX}})}$$

where C_{AB} is the confidence candidate A assigns to the trust relation t_{AB} and X_{MAX} is the user with the maximum confidence assigned by A .

It is worth mentioning that this counts only for similarity-based trust. In the case of explicit trust the confidence value is of course always set to 1 as we assume the individual to have full confidence in his own explicit trust rating.

Let $p \in P = \{p_1, \dots, p_q\}$ be a trust path between two candidates, $N = \{N_i : i = 1, 2, \dots, k\}$ all intermediate nodes in the trust path p and $ET' = t'_{y,y,v}$ the matrix containing the explicit trust ratings (see section 3.2). Using the confidence values as trust paths weights and combining the explicit and similarity based trust calculation models, we get the following formulation to calculate a predicted trust rating t'_{AB} :

$$t'_{AB} = \sum_{p \in P} \left(\frac{C_{AN_1} \cdot C_{N_1N_2} \cdot \dots \cdot C_{N_kB}}{\sum_{p \in P} C_{AN_1} \cdot C_{N_1N_2} \cdot \dots \cdot C_{N_kB}} t_{AN_1} \Diamond t_{N_1N_2} \Diamond \dots \Diamond t_{N_kB} \right)$$

$$\text{with } C_{XY} = \begin{cases} 1 & \text{if } t_{XY} \in ET' \\ \frac{n(I_X \cap I_Y)}{n(I_X \cap I_{X_{MAX}})} & \text{otherwise} \end{cases} \text{ and}$$

$$t_{(X-1)X} \Diamond t_{X(X+1)} = \begin{cases} \frac{n(I_{X-1} \cap I_X)}{n(I_{X-1} \cap I_X) + n(I_X \cap I_{X+1})} t_{(X-1)X} + \frac{n(I_X \cap I_{X+1})}{n(I_{X-1} \cap I_X) + n(I_X \cap I_{X+1})} t_{X(X+1)} & \text{if } t_{(X-1)X} \text{ and } t_{X(X+1)} \notin E \\ t_{(X-1)X} \cdot t_{X(X+1)} & \text{otherwise} \end{cases}$$

Figure 3 shows an example of explicit and similarity-based trust calculation. Utilizing the above described concatenation and aggregation rules we finally get a predicted value for trust relation t'_{AD} as depicted below.

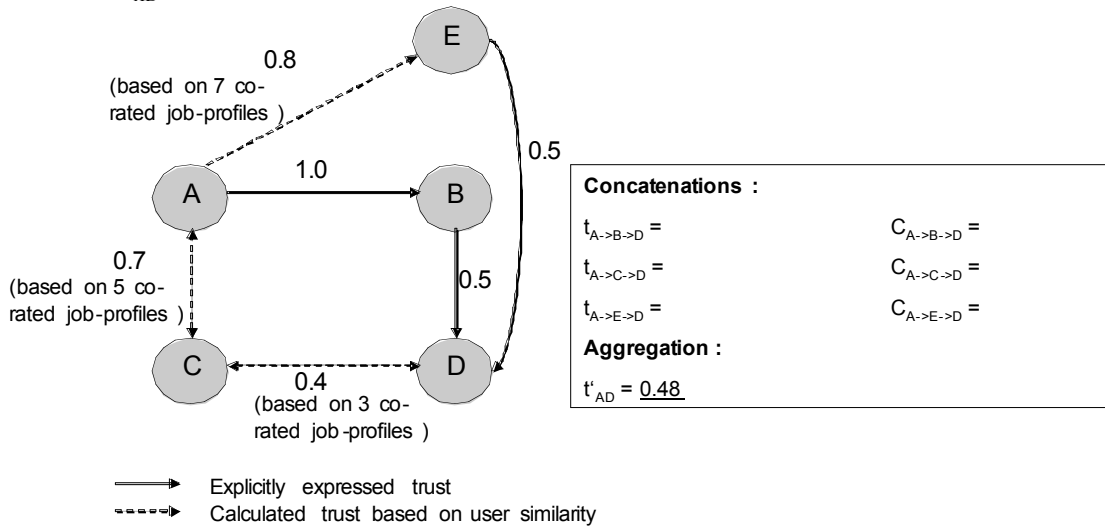


Figure 3: Explicit and similarity-based trust calculation

In a team configuration scenario, we can now calculate the trust values t_{M^*A} with $M^* = \{M_i; i = 1, 2, \dots, k\}$ being a set of existing team members. The calculated trust values for each single team member are summed up and divided through the number of members:

$$t_{M^*A} = \frac{\sum_{M_i \in M^*} t_{M_iA}}{n_{M^*}}$$

with n_{M^*} being the number of existing team members.

4. Incorporating Trust into a Recommender-Based Approach

In the preceding sections we presented an existing probabilistic model to recommend candidates that fit best to a job based on unary attributes (person-job fit). We discussed the need for extending the model to incorporate trust as relational aspect. Thus we presented a trust computational model to calculate a relational fit based on explicit and similarity-based trust values (person-team fit). Figure 4 shows the process of integrating both approaches to an integrated recommendation approach.

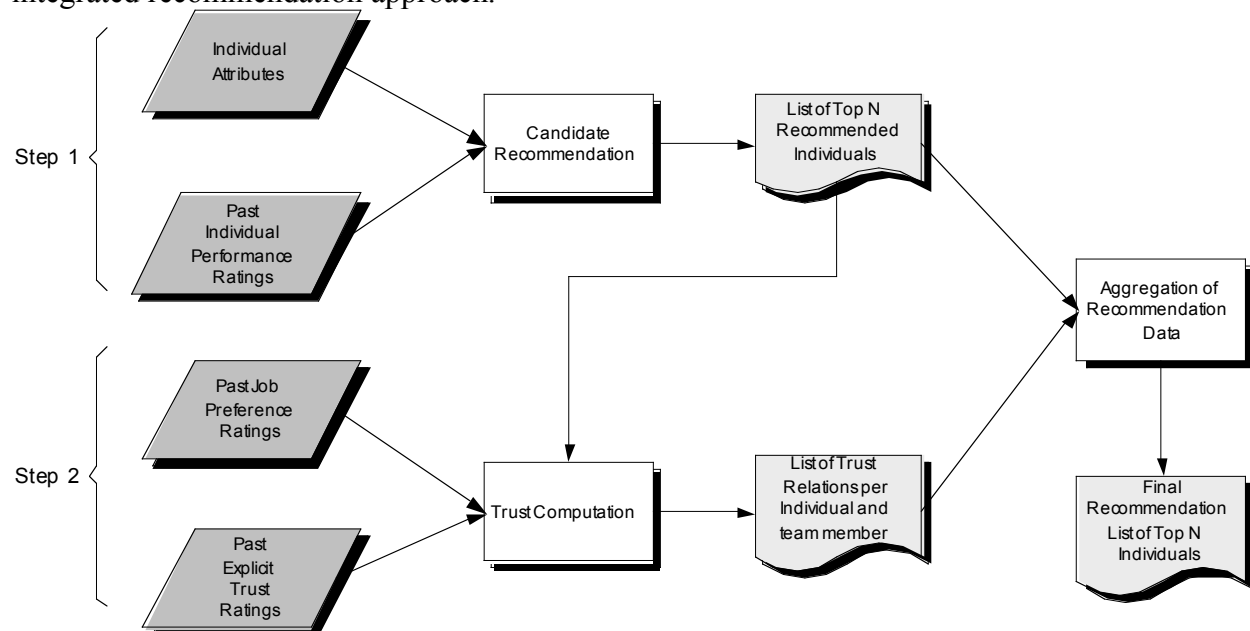


Figure 4. The Recommendation Process

In step 1 we use the adapted PLSA model to recommend candidates whose skills, knowledge and abilities as well as general mental abilities and personality fit best to a given job profile. The generated list of top N recommended candidates is used as input for step 2 where we utilize the trust computational model to calculate trust ratings between the individuals and all existing team members. In the last step we aggregate all recommendation data leading to a final list of recommended candidates that fit best to the given job profile as well as to existing team members in terms of trust. As we have two separate lists based on the preferences of the recruiter as well as of the existing team members, the aggregation is not an easy task as it implies intersubjective comparability of preferences in the sense that recruiter x 's preferences for candidate y has to be compared with the trust preferences of all team members.

Theoretical considerations as well as practical experience let us assume that the priority of each of the two perspectives (person-job and person-team fit) depends on the type of job. However, further research needs to be done in this area in order to find an optimal aggregation rule. For a first implementation we decided to give priority to the preferences of

the recruiter to select a number of top N candidates and then in a second step rank those candidates by the trust ratings assigned from existing team members. To get an aggregated rating value we use the following formulation:

$$R' = (r'_{x,y,v}) = \alpha \cdot t'_{M^*y} \cdot (1 - \alpha) \cdot r'_{x,y,v}$$

with α set to 0.5.

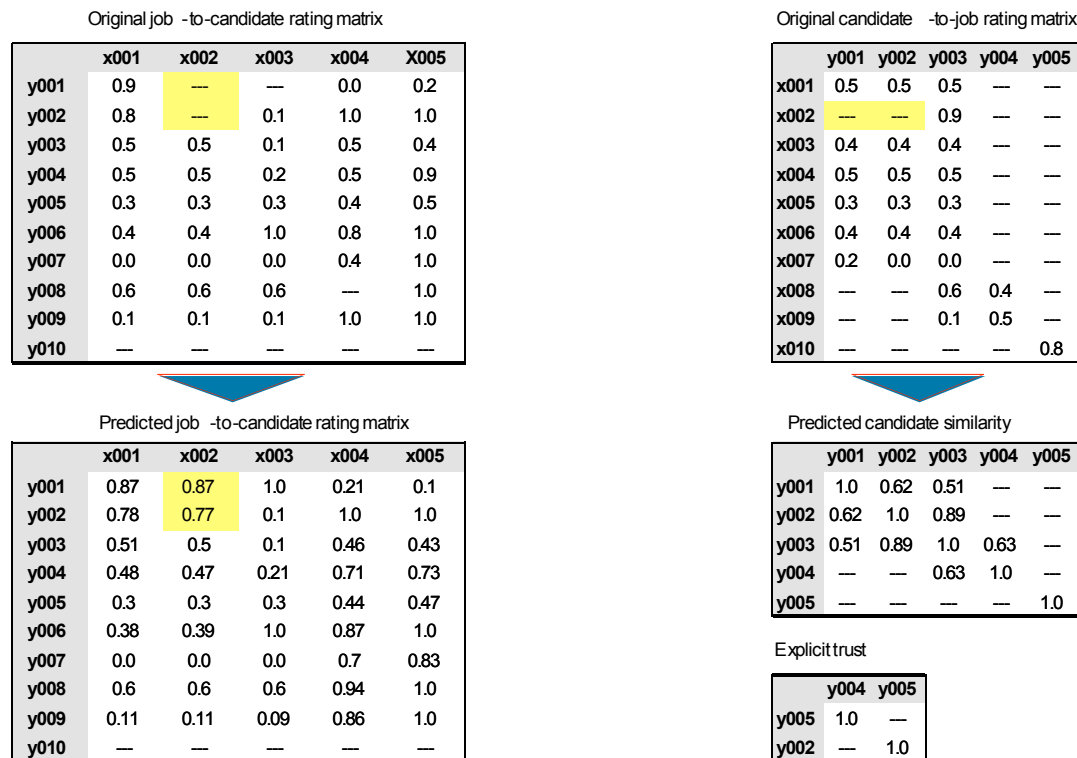
In the following we present results from first validations with synthetic data.

4.1. Results from test runs with synthetic data

Based on the defined requirements we implemented the described model in a first prototype aiming to verify our findings. The prototype is implemented as a standalone application that is built upon a relational data model capturing the candidate profiles, as well as the past ratings and trust values. The data is stored in a local database and used as input for the recommendation process. In a first step, the PLSA model for partner recommendation has been developed and validated based on the approach as described by Färber et al. (2003). Afterwards we implemented the trust computational model. Finally we integrated both models to a complete and full functioning prototype for IS-supported team building.

In order to validate the implementation and its underlying model, we first conducted a pre-test with synthetic data. We created 50 job and 50 candidate profiles each consisting of several attributes. Additionally we generated fictive preference ratings (normalized to values between 0 and 1) for candidates in order to train the PLSA model allowing us to predict so far unknown candidate ratings. Explicit as well as similarity-based trust ratings are used as input for the trust computational model to predict trust relations between so far unknown individuals.

Figure 5 shows a subset out of the synthetic dataset to visualize the results from our prototype pre-test.



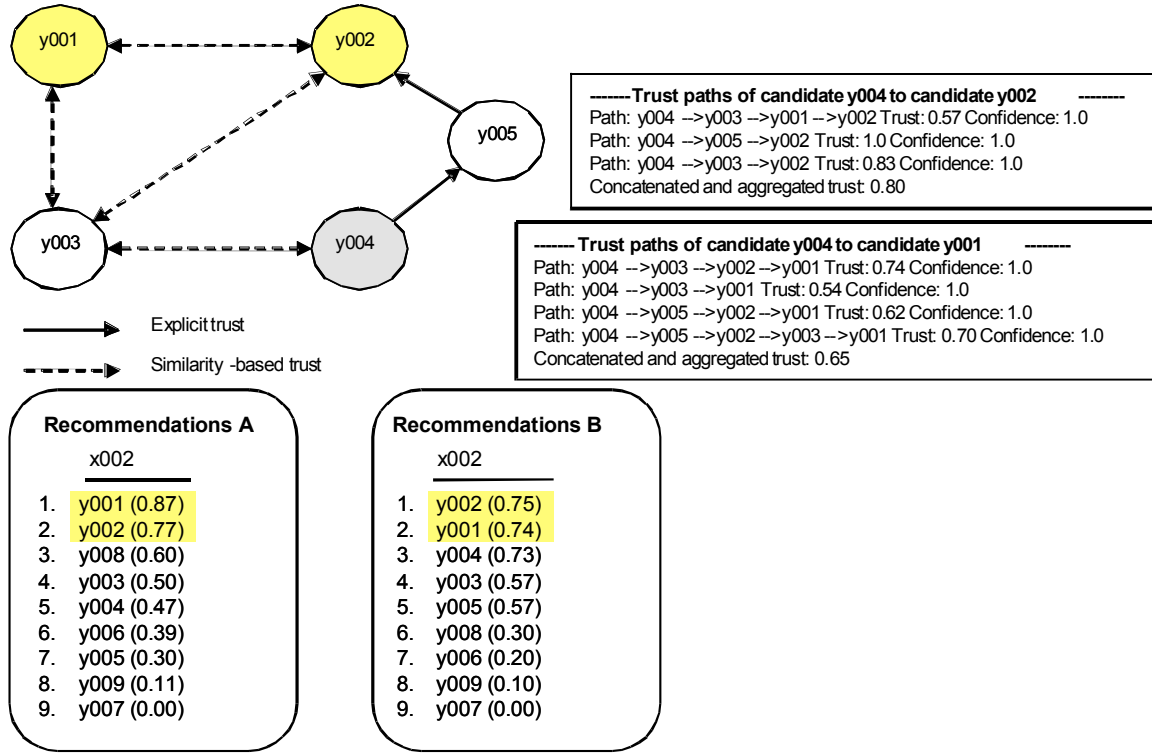


Figure 5: Example of the recommendation approach

The example as depicted in the above figure, describes the following team building scenario: The recruiter aims to find a candidate $y \in Y = \{y001, \dots, y010\}$ that fits best to the requirements of job profile $x002 \in X = \{x001, \dots, x010\}$ as well as to the existing team consisting of team member $m = y004$. We choose three as dimension of the latent aspect used in the PLSA models.

In a first step we train the probabilistic model with past candidate ratings as depicted in the upper left matrix. Using the EM algorithm we get the matrix of *predicted job-to-candidate* ratings. As can be seen, the model detects the rating similarity between $x001$ and $x002$ leading to a similar predicted value for the previously not rated candidates $y001$ and $y002$. The model is not able to capture the very small differences of the rating values as the number of latent aspects is smaller than the number of candidates (Hofmann 1999). Based on the predicted rating matrix we can generate a first recommendation list (*Recommendations A* in the above figure).

In a second step we include trust as relational aspect. The two explicit (between $y004$ and $y005$ as well as between $y005$ and $y002$) and four similarity-based trust ratings, derived from the *predicted candidate similarity* matrix, whose entries are based on similarities in the *candidate-to-job* ratings, are used to run the trust computation. As results we get calculated trust values between the individuals in question as depicted in the visualized trust paths of the above figure.

Finally we combine the recommendation list as created with the PLSA model with the recommendations as calculated with the trust computational model leading to a final recommendation list (*Recommendations B* in the above figure).

5. Conclusion and Further Research

The selection of individuals to teams is currently only rarely supported by information systems as search and filter techniques mainly consist of simple keyword-based database queries or only cover unary attributes tied to an individual. The latter do not embrace

relational aspects that are important to determine a good fit. At the same time organizational structures are changing and teams need to be composed more often. Motivated by this we presented a novel recommendation approach to support the team building. Compliant with findings from research on person-job and person-team fit we conclude that an automated recommendation approach needs to integrate unary candidate attributes as well as relational information. Some parts of the required data can be derived from personal profiles that are electronically stored already in many human resource systems.

Considering these requirements, we developed a trust computational model thus incorporating trust into an existing recommender-based approach that is based on a probabilistic latent aspect model. This enables us to capture individual as well as relational attributes serving as input for our novel decision support system prototype. We believe our research has important practical implications as it can support managers and recruiters in the effective composition of teams.

It should be stressed that our approach is not meant to replace traditional selection methods but is meant to support the team building scenario by pre-selecting a list of candidates from which the HR-expert could then choose the preferred ones based on human judgment.

Despite being in an early research stage, the pre-tests with synthetic data lead to promising results. As part of our ongoing research in this area, we aim to further validate the approach with real-life data derived from a planned student workshop as well as with employee and staffing data from a big consulting company. In addition we want to enhance our prototype by including information from an individual's position within the network as an additional variable of the model and extend it by various relation types other than trust.

References

- Abdul-Rahman, A. and Hailes, S. "Supporting trust in virtual communities," *Proceedings of the 33rd Hawaii International Conference on System Sciences*, Maui, Hawaii, USA, January 4-7, 2000.
- Albert, G. *Betriebliche Personalwirtschaft*, 6th edition, Friedrich Kiel Verlag, Ludwigshafen, Germany, 2004.
- Anderson, N., Lievens, F., van Dam, K. and Ryan, A. M. "Future Perspectives on Employee Selection: Key Directions for Future Research and Practice," *Applied Psychology: An International Review* (53:4), 2004, pp. 487-501.
- Autor, D. H. "Wiring the labor market", *Journal of Economic Perspectives* (15: 1), Winter 2001, pp. 25-40.
- Beck, C. *Professionelles E-Recruiting: Strategien-Instrumente-Beispiele*, Neuwied, Krikel:Luchterhand, 2002.
- Breese, J. S., Heckerman, D. and Kadie, K. "Empirical analysis of predictive algorithms for collaborative filtering," *Proceedings of the 14th Conference on Uncertainty in Artificial Intelligence (UAI)*, 1998, pp. 43-52.
- Chatman, J. A. "Improving interactional organization research: A model of person-organization fit," *Academy of Management Review*, 14, 1989, pp. 333-349.
- Cho, T. S., Hambrick, D. C. and Chen, M.-J. "Effects of Top Management Team Characteristics on Competitive Behavior of Firms," *Academy of Management Proceedings*, 1994, pp. 5-17.
- Dempster, A. P., Laird, N. M. and Rubin, D. B. "Maximum likelihood from incomplete data via the EM algorithm," *J. Royal Statist. Soc., B* 39, 1977, pp. 1-38.
- DeSanctis, G., and Monge, P. "Introduction to the special issue: communication processes for virtual organizations", *Organization Science* (10: 6), November-December 1999, pp. 693-703.

- DiTomaso, N. "The loose coupling of jobs: the subcontracting of everyone," *Sourcebook of Labor Markets: Evolving Structures and Processes*, Berg, I. and Kalleberg, A.L. (Eds.), Kluwer Academic/Plenum, New York, 2001, pp. 247-270.
- Dunphy, D. and Bryant, B. "Teams: Panaceas or prescriptions for improved performance?" *Human Relations*, 49, 1996, pp. 677-699.
- Evans, C. R. and Dion, K.L. "Group cohesion and performance: A meta-analysis," *Small Group Research*, 22, 1991, pp. 175-186.
- Färber, F., Keim, T. and Weitzel, T. "An Automated Recommendation Approach to Personnel Selection", *Proceedings of the 2003 Americas Conference on Information Systems*, Tampa, USA, 2003.
- Guha, R., Kumar, R., Raghavan, P. and Tomkins, A. "Propagation of Trust and Distrust," *Proceedings of the World Wide Web*, New York, USA, May 17-22, 2004.
- Guzzo, R. A. "Fundamental considerations about work groups", *Handbook workgroup psychology*, West, M.A. (ed.), Chichester, UK: John Wiley & Sons, 1996, pp. 3-21.
- Herlocker, J. L., Konstan, J. A., Borchers, A., and Riedl, J. "An Algorithmic Framework for Performing Collaborative Filtering," *Proc. of the 22nd ACM SIGIR Conference on Research and Development in Information Retrieval*, 1999.
- Hofmann, T. "Probabilistic latent semantic analysis," *Proceedings of the 15th Conference on Uncertainty in Artificial Intelligence (UAI)*, July 30-August 1, Stockholm, Sweden, 1999, pp. 289-296.
- Hofmann, T. and Puzicha, J. "Latent class models for collaborative filtering," *Proceedings of the 16th International Joint Conference on Artificial Intelligence*, July 31 – August 6, Stockholm, Sweden, 1999, pp. 688-693.
- Jackson, S. E. "The consequences of diversity in multidisciplinary work teams," in *Handbook of workgroup psychology*, West, M.A. (eds.), John Wiley & Sons, Sussex, 1996.
- Jones, G. R. and George, J. M. "The experience and evolution of Trust: Implications for Co-operation and Teamwork," *The Academy of Management Review*, Vol. 23 No. 3, 1998, pp. 531-546.
- Kamvar, S. D., Schlosser, M. T. and Garcia-Molina, H. "The eigentrust algorithm for reputation management in P2P networks," *Proceedings of the 12th International World Wide Web Conference*, 2003, pp. 640-651.
- Keim, T., König, W., von Westarp, F., Weitzel, T. and Wendt, O. "Recruiting Trends 2005 - Eine empirische Untersuchung der Top-1.000-Unternehmen in Deutschland und von 1.000 Unternehmen aus dem Mittelstand", *Working paper*, Frankfurt am Main, Germany, 2005.
- Khare, R. and Rifkin, A. "Weaving a Web of Trust," *WWW Journal*, Volume 2, Number 3, 1997, pp. 77-112.
- Kristof, A. L. "Person-organization fit: An integrative review of its conceptualizations, measurement, and implications," *Personnel Psychology*, 49 (1), 1996, pp. 1-49.
- Lang, A. and Pigneur, Y. "Digital trade of human competencies", *Proceedings of the 32nd Annual Hawaii International Conference on System Sciences*, Hawaii, USA, 1999, pp. 165-173.
- McAllister, D. J. "Affect- and cognition-based trust as foundations for interpersonal cooperation in organizations," *Academy of Management Journal*, 38, 1995, pp. 24-59.
- Montaner, M., Lopez, B. and de la Rosa, J. "Opinion-based filtering through trust," *Proceedings of the Sixth International Workshop on Cooperative Information Agents*, Madrid, Spain, September 2002, pp. 164-178.
- Muchinsky, P. M. and Monahan, C. J. "What is person-environment congruence? Supplementary versus complementary models of fit", *Journal of Vocational Behavior*, 31, 1987, pp. 268-277.

- Papagelis, M., Plexousakis, D. and Kutsuras, T. "Alleviating the Sparsity Problem of Collaborative Filtering Using Trust Inferences," To appear in: *The 3rd international conference on trust management, iTrust*, 2005.
- Popescul, A. and Ungar, L. H., Pennock, D. M. and Lawrence, S. "Probabilistic models for unified collaborative and content-based recommendation in sparse-data environments," *Proceedings of the Seventeenth Conference on Uncertainty in Artificial Intelligence*, Seattle, USA, August 2001, pp. 437-444.
- Resnick, P. and Varian, H. R. "Recommender systems," *Communications of the ACM*, 40 (3), 1997, pp. 56-58.
- Richardson, M., Agrawal, R. and Domingos, P. "Trust management for the semantic web," *Proceedings of the Second International Semantic Web Conference*, Sanibel Islands, USA, October 20-23, 2003, pp. 351-368.
- Salgado, J. F. "Personnel Selection Methods," *International Review of Industrial and Organizational Psychology*, 14, 1999, pp. 1-54.
- Salgado, J. F., Anderson, N., Moscoso, S., Bertua, C., De Fruyt, F., and Rolland, J. P. "A meta-analytic study of general mental ability validity for different occupations in the European Community," *Journal of Applied Psychology*, 2003.
- Sarwar, B., Karypis, G., Konstan, J. and Riedl, J. "Item-based collaborative filtering recommender algorithms," *Proceedings of the 10th International World Wide Web Conference*, 2001, pp. 285-295.
- Tihanyi, L., Ellstrand, A. E., Daily, C. M. and Dalton, D. R. "Building of the Top Management Team and Firm International Diversification," *Journal of Management*, Vol. 26, No. 6, 2000, pp. 1157-1177.
- Tziner, A. E. "Effects of team building on ranked team effectiveness: The blocked fractional design," *Small Group Behavior*, 19, 1988, pp. 363-378.
- Watson, W. E., Kumar, K. and Michaelsen, L. K. "Cultural diversity's impact on interaction process and performance: Comparing homogeneous and diverse task groups," *Academy of Management Journal*, 36, 1993, pp. 58-79.
- Werbel, J. D. and Gilliland, S. W. "Person-environment fit in the selection process," in *Research in Personnel and Human Resource Management*, Ferris, G. R. (eds.), Vol. 17, Stamford, CT: JAI Press, 1999, pp. 209-243.
- Werbel, J. D. and Johnson, D. J. "The use of person-group fit for employment selection: A missing link in person-environment fit," *Human Resource Management*, Vol. 40, No. 3, 2001, pp. 227-240.
- West, M. A. *Effective teamwork*, Leicester, UK, BPS Books, 1994.
- Xin J., Yanzan, Z. and Mobasher, B. "Web usage mining based on probabilistic latent semantic analysis," *Proceedings of the 2004 ACM SIGKDD international conference on Knowledge discovery and data mining*, Seattle, WA, USA, 2004, pp. 197 - 205.
- Yu, B and Singh, M. P. "A Social Mechanism of Reputation Management in Electronic Communities," in *Cooperative Information Agents IV, Lecture Notes in Artificial Intelligence*, M. Klusch and L. Kerschberg (eds.), Vol. 1860, Springer-Verlag, Berlin, 2000, pp. 154-165.
- Yu, B. and Singh, M. P. "Social networks and trust: Detecting deception in reputation management," *Proceedings of the second international joint conference on Autonomous agents and multiagent systems*, Melbourne, Australia, July 14-18, 2003, pp. 73-80.
- Ziegler, C. N. and Lausen, G. "Analyzing Correlation Between Trust and User Similarity in Online Communities," *Proceedings of the 2nd International Conference on Trust Management*, 2004.